



# Jigsaw: Indoor Floor Plan Reconstruction via Mobile Crowdsensing

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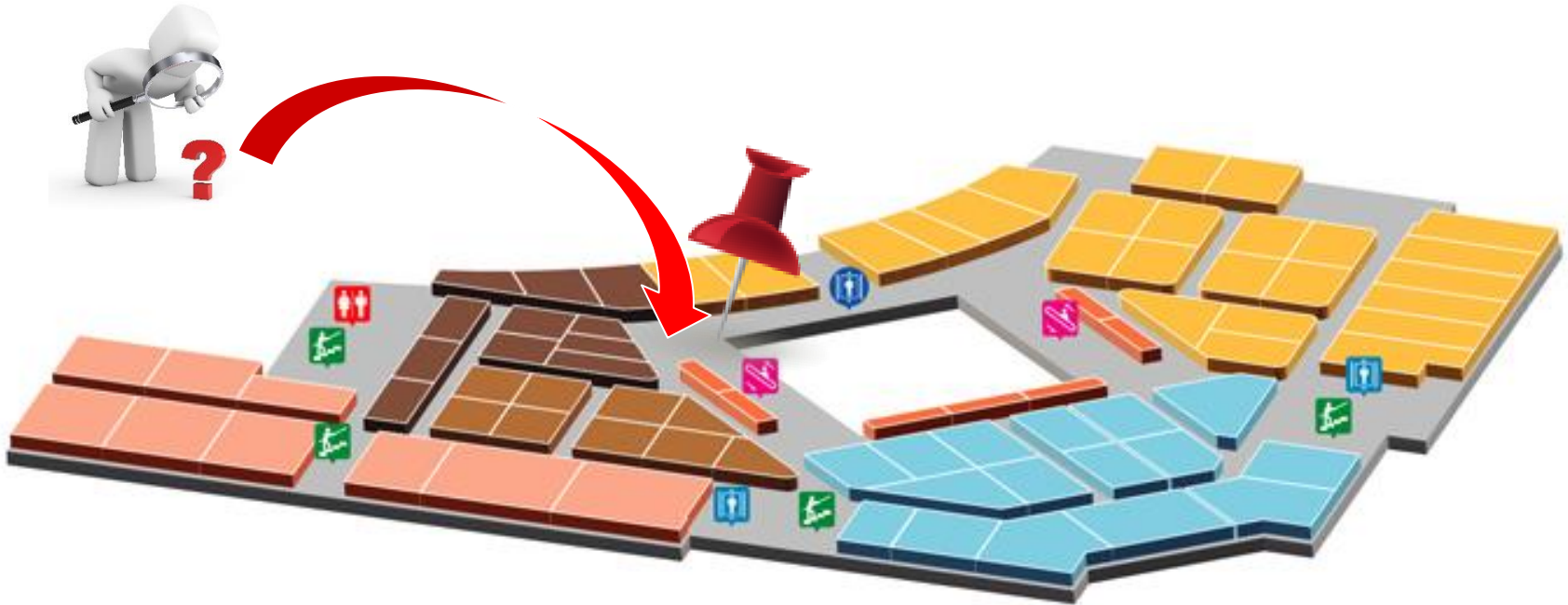
**ACM MobiCom 2014**

**Maui, HI, USA**



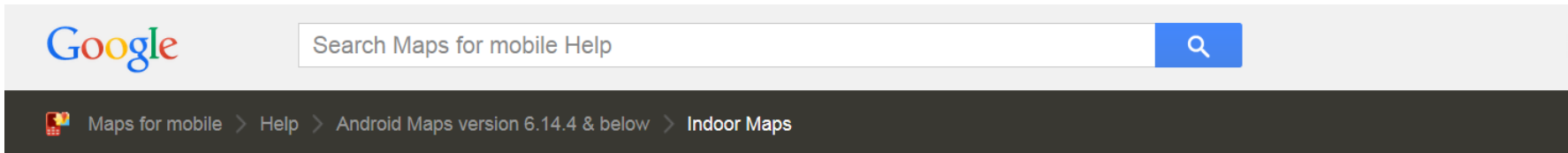
# ***Jigsaw: Floor plan reconstruction***

## ◆ Motivation



# Jigsaw: Floor plan reconstruction

## ◆ Motivation



## Indoor Maps availability

Indoor maps are currently available in selected locations. Check back as more locations are added, or [upload a floor plan](#). Over **10,000 floor plans** available from the following countries:

<a href="#">+</a>	Australia
<a href="#">+</a>	Austria
<a href="#">+</a>	Belgium
<a href="#">+</a>	Canada
<a href="#">+</a>	Denmark
<a href="#">+</a>	France
<a href="#">+</a>	Germany
<a href="#">+</a>	Hong Kong
<a href="#">+</a>	India

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# ***Jigsaw: Floor plan reconstruction***

## ◆ Motivation

## ◆ Crowdsensing based construction

- Gather piecewise data from individual mobile users
  - e.g., images, inertial sensor data
- Extract floor plan information
- Put pieces together into a complete floor plan



## ◆ Benefits

- Service providers (e.g., Google) don't need to negotiate with building owners one by one
- No need to hire dedicated personnel for inch-by-inch measurements either



# ***Crowsensing to construct floor plan***

## ◆ **Challenges**

- **Accurate coordinates and orientations of indoor landmarks (i.e., POIs such as store entrances)**
  - Inertial data couldn't provide
- **Insufficient “anchor points”**
  - Error accumulation in dead reckoning
  - Over- and under- estimation of accessible areas

## ◆ **Inspiration**

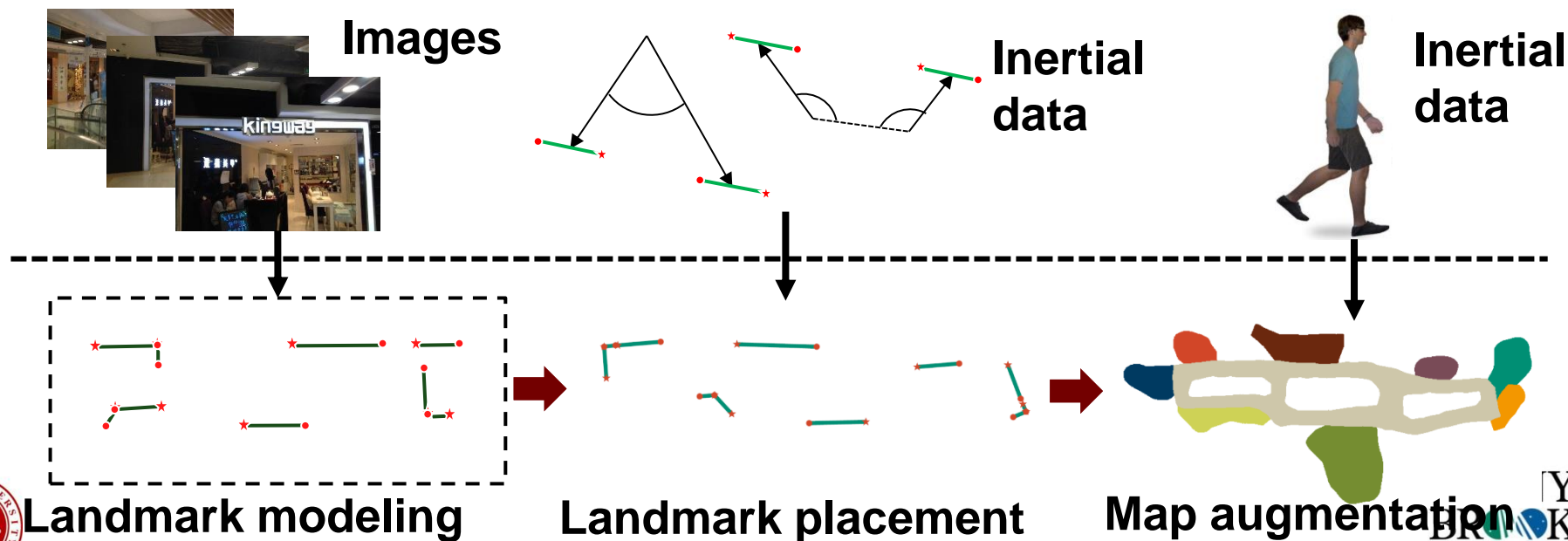
- **Complementary strengths of vision and mobile techniques**
  - Vision ones to produce accurate geometric information for landmarks
  - Inertial data to obtain placement of landmarks, and less critical hallway and room shapes
- **Use optimization and probabilistic formulations**
  - Robustness against errors/noises from data



# Jigsaw overview

## ◆ Three stages

- Landmark modeling: extract landmark geometry from images
- Landmark placement: obtain pairwise landmark spatial relation (e.g., distance, orientation) from inertial data
- Map augmentation: construct hallway and room shapes from mobile traces



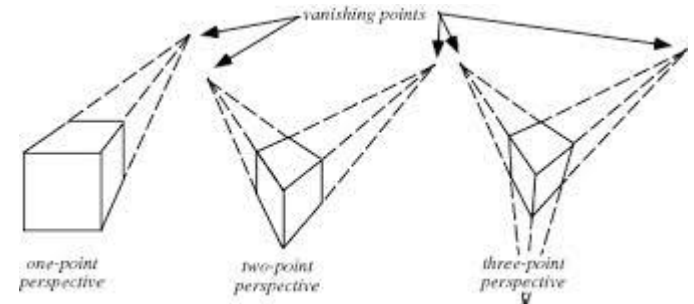
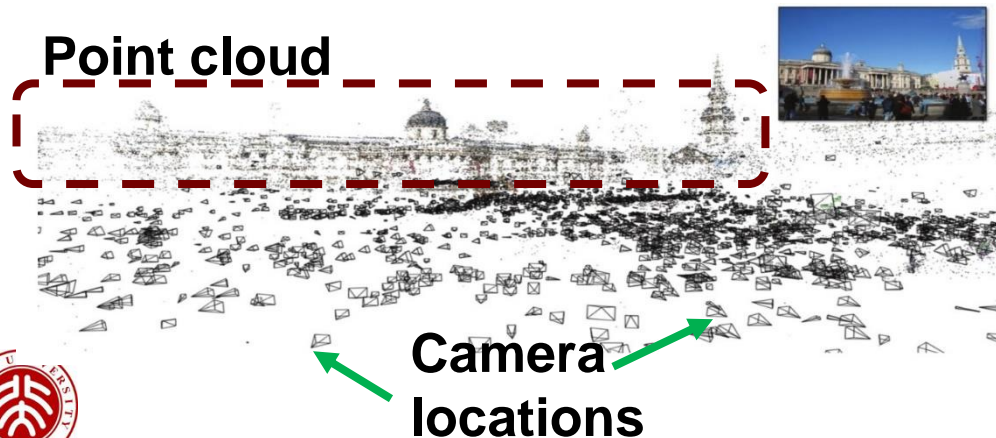
# Landmark modeling

## ◆ Goal

- Extract sizes and coordinates of major geometry features (e.g., widths of entrances, lengths/orientations of walls) of landmarks

## ◆ Method: extend two computer vision techniques

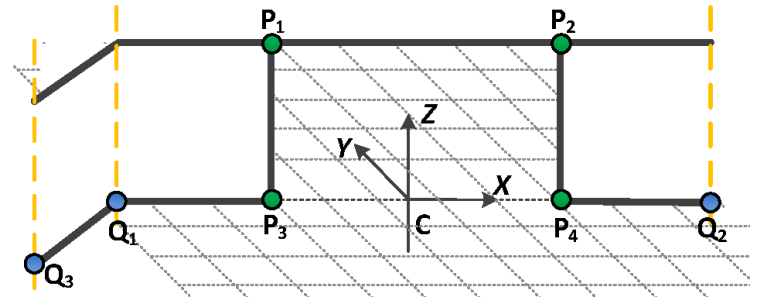
- Structure from Motion(SfM): given a set of images of the same object from different viewpoints, generate (in the LOCAL coordinate system)
  - 1) a “cloud” of 3d points representing the exterior shape of the object;
  - 2) the location where each image is taken
- Vanishing line detection: given an image, detect orthogonal line segments of the object



# Landmark modeling process(1/2)

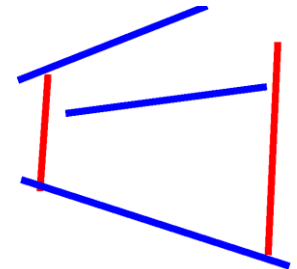
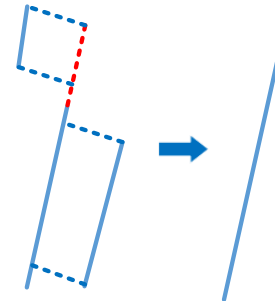
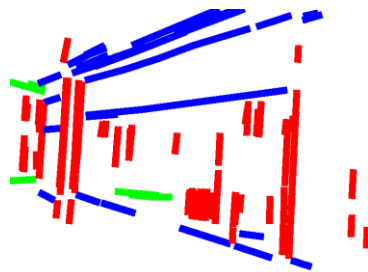
## ◆ Geometric vertices

- P: four corners of a store entrance
- Q: connecting points of wall segments



## ◆ Extract the coordinates of geometric vertices

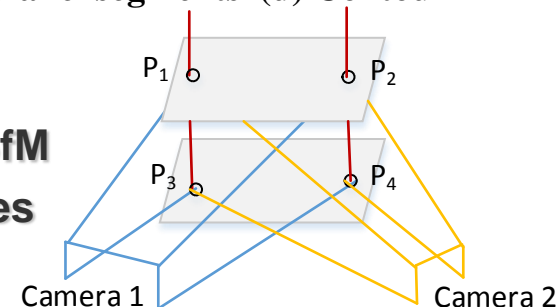
- Step 1. Extract landmark's major contour lines on each image



(a) Original image (b) Vanishing line detection (c) Merge co-linear and parallel segments (d) Contour

## ▪ Step 2. Project 2D lines into 3D

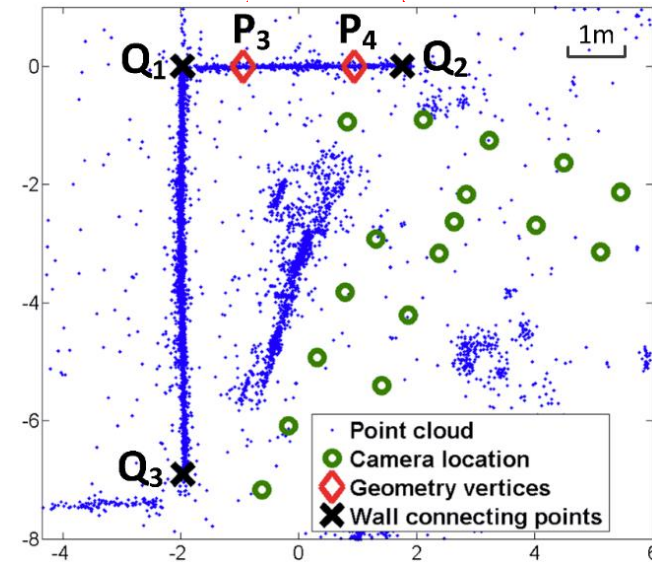
- Project 2D lines using transformation matrices by SfM
- Use adapted k-means to cluster major geometry lines



# Landmark modeling process(2/2)

## ◆ Detect connecting points of wall segments

- Project the 3d point cloud onto XY plane
- Detect wall segments and their connecting points
  - Use entrance line ( $P_3P_4$ ) from the previous step as the start
  - Find the two ends( $Q_1Q_2$ )
  - Continue to search for more connecting point ( $Q_3$ )



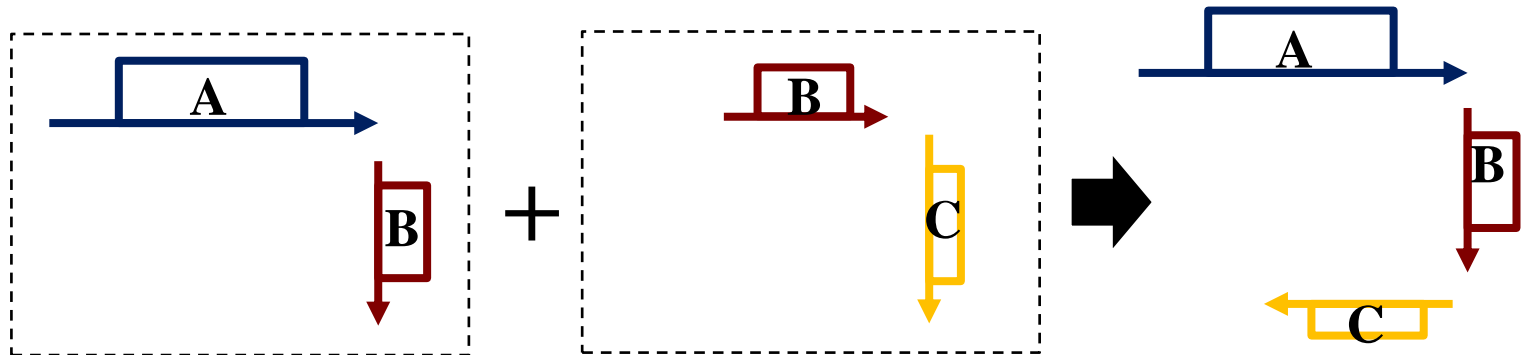
# Landmark placement

## ◆ Goal



- **Input: landmark models in their local coordinate systems**
  - Major geometry features, positions of cameras
- **Output: landmarks placed on a global coordinate system**
  - Absolute coordinates and orientations

## ◆ Method



- **Step 1. Obtain pairwise spatial relationship between adjacent landmarks**
- **Step 2. place adjacent landmarks on the common ground**



# Micro-tasks for spatial relationships

## ◆ A series of data gathering actions

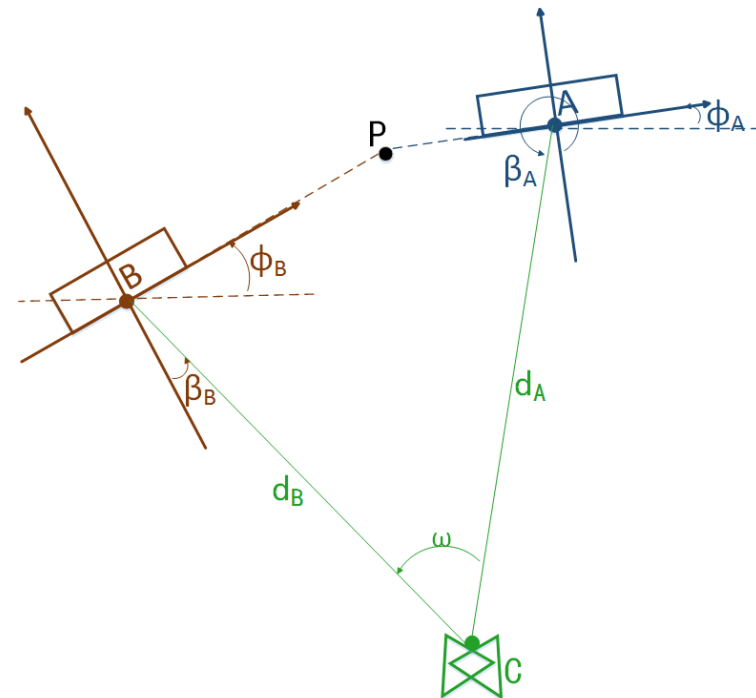
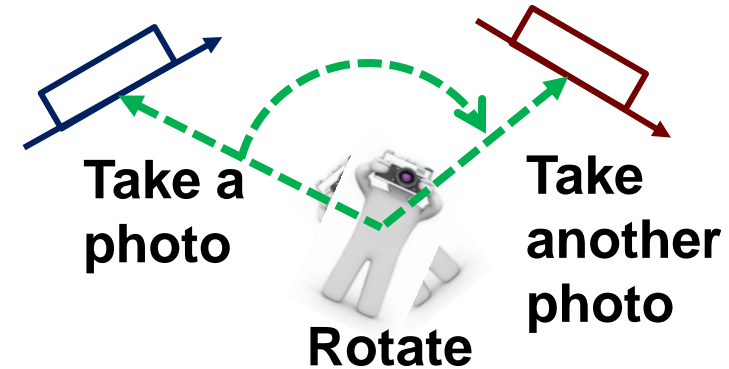
- Obtain pairwise distance and orientation constraints

## ◆ Click-Rotate-Click(CRC)

- $\omega$ : rotated angles from gyroscope
- $(d_A, \beta_A)$  and  $(d_B, \beta_B)$  : SfM output
- Relative distance and orientation between A,B uniquely determined

## ◆ Click-Walk-Click(CWC)

- $|C_A C_B|$ : step counting
- $\omega_A$  and  $\omega_B$ : placement offset estimation and gyroscope readings
- $(d_A, \beta_A)$  and  $(d_B, \beta_B)$  : SfM output
- Similar measurements calculation

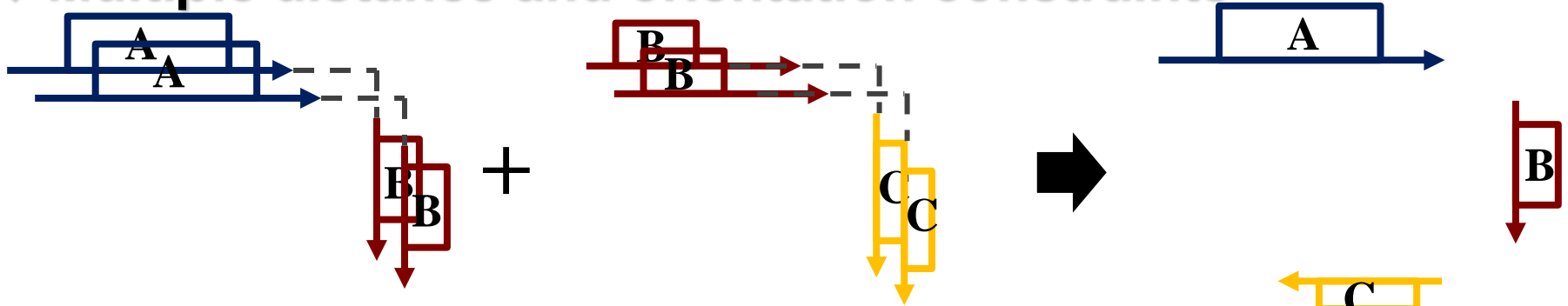






# Landmark placement formulation

## ◆ Multiple distance and orientation constraints



## ◆ Maximum Likelihood Estimation (MLE)

- $\Theta^*$ : the most likely coordinates and orientations
  - $\Theta = \{X, \phi\}$ : coordinates and orientations of landmarks
  - $Z, O$ : observations of  $X, \phi$

$$\theta^* = \arg \max_{\theta} P(Z, O | X, \phi)$$

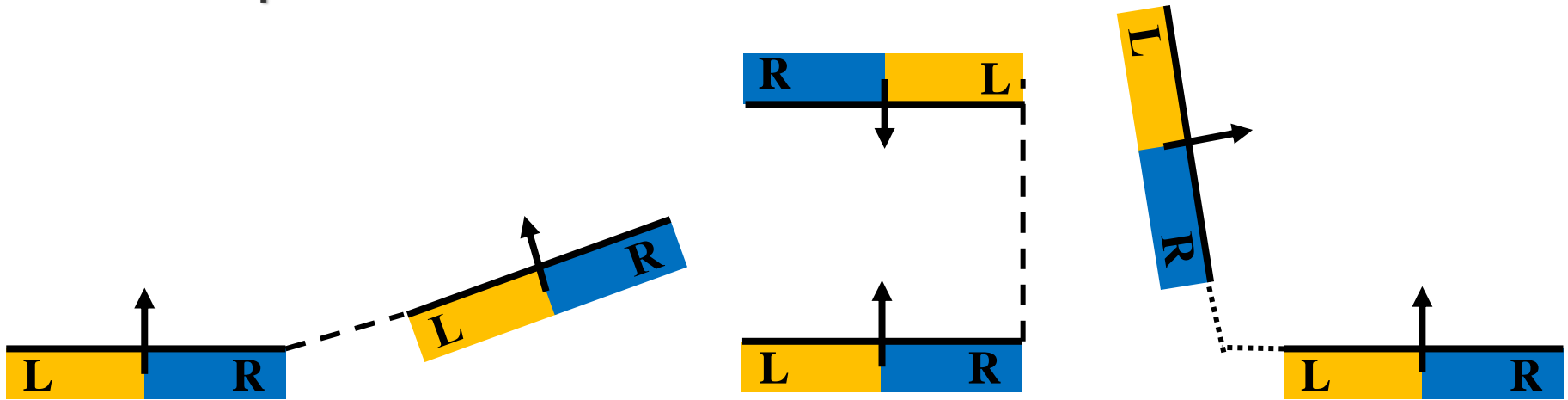
## ◆ Landmark placement results



# Hallway boundary construction

## ◆ Two connection options

- Direct line between two segments
  - collinear or facing each other
- Extend two segments to an intersection point
  - Perpendicular walls



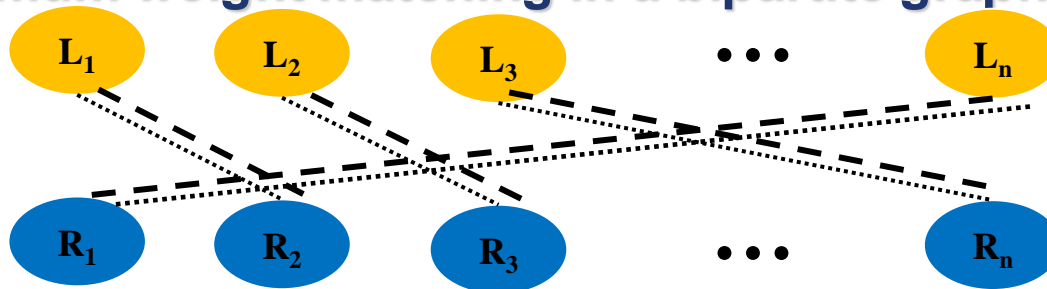
# Hallway boundary construction

## ◆ Two connection options

- Direct line between two segments
  - collinear or facing each other
- Extend two segments to an intersection point
  - Perpendicular walls

## ◆ Problem formulation

- Minimum weight matching in a bipartite graph.



- Solution: Kuhn-Munkres algorithm\*
  - $O(n^3)$ ,  $n$ : number of landmarks

# Compare with alternative methods

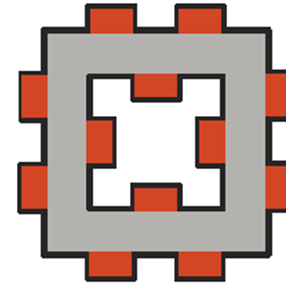
## ◆ Naïve convex hull

- Miss segments inside

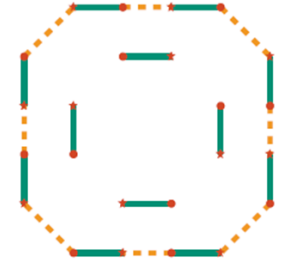
## ◆ Greedy algorithms

- Depend on order of connecting
- Miss 90° corners

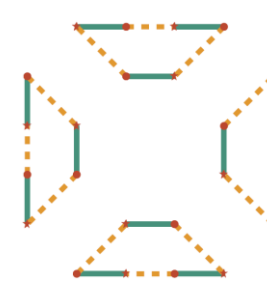
## ◆ Our results



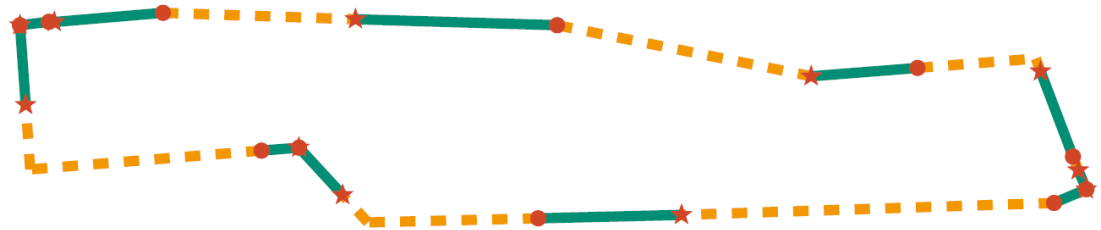
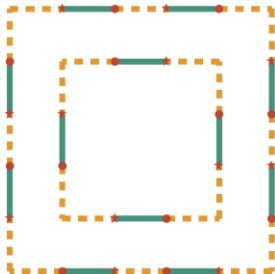
Example scenario



convex hull



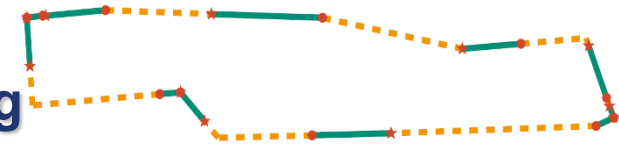
Greedy method results



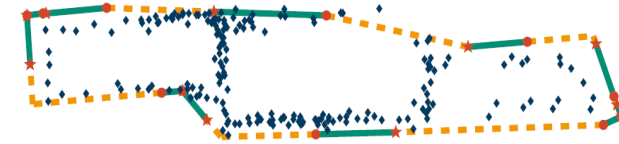
# Details reconstruction: hallway shape

## ◆ Step 1. build *occupancy grid map*

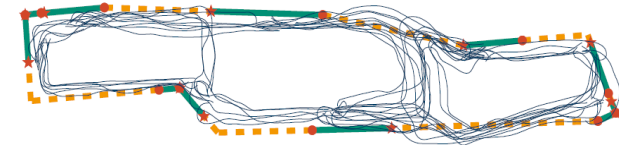
- Grid cells each with a variable representing the probability it is accessible
- a) External boundary of hallway
- b) Camera positions
- c) Trajectories



**External boundary**



**+ Camera positions**



**+ User trajectories**

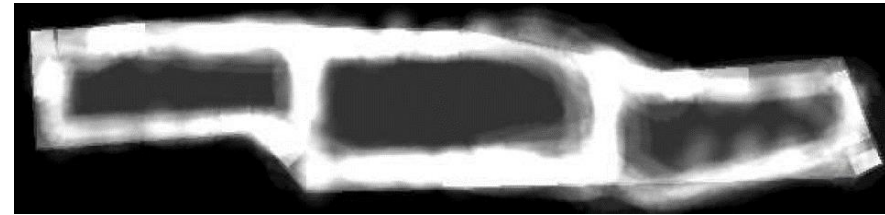
# Details reconstruction: hallway shape

## ◆ Step 1. build occupancy grid map

- Grid cells each with a variable representing the probability it is accessible

- a) External boundary of hallway
- b) Camera positions
- c) Trajectories

Occupancy map



## ◆ Step 2. Binaryzation with a threshold

## ◆ Step 3. Smoothing

- Alpha-shape\*



Thresholding



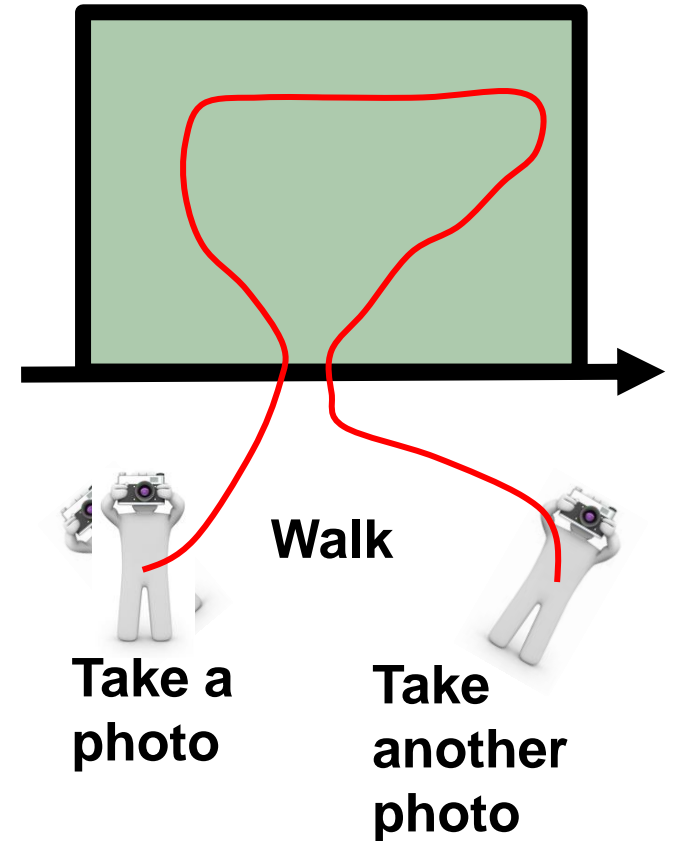
Smoothing



# ***Details reconstruction: room shape***

## ◆ Room reconstruction

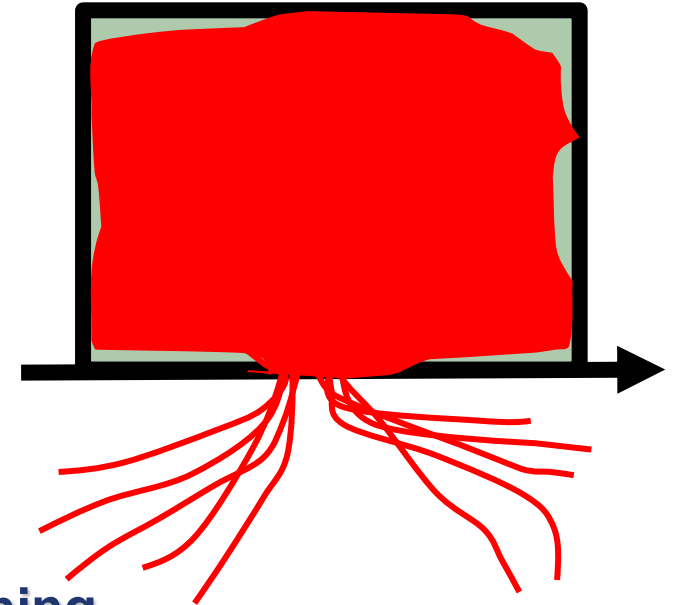
- Data-gathering micro-task
  - CWC inside one room
- Step 1. determine initial/final locations
  - Two camera locations as anchor points



# Details reconstruction: room shape

## ◆ Room reconstruction

- Data-gathering micro-task
  - CWC inside one room
- Step 1. determine initial/final locations
  - Two camera locations as anchor points
- Step 2. use trajectories to build an occupancy grid map
- Step 3. similar thresholding and smoothing



## ◆ Results



Stores



Combined hallway, stores

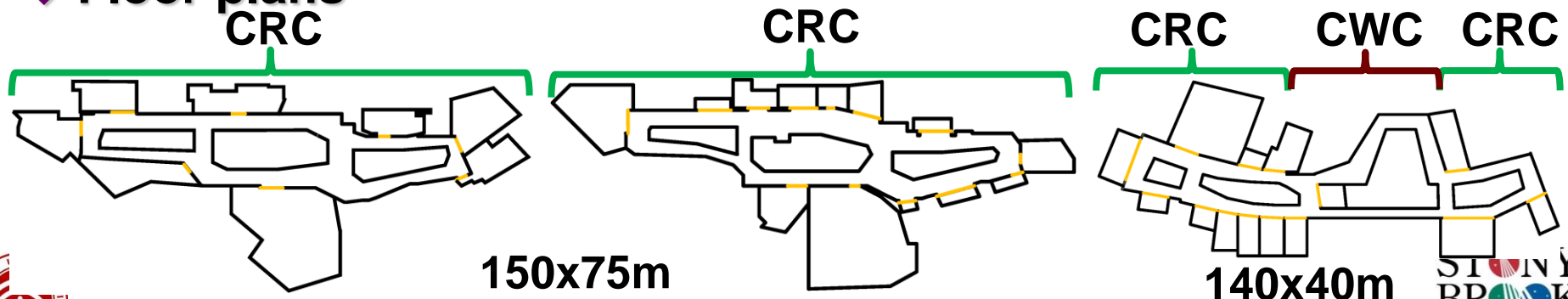
# Evaluation

## ◆ Methodology

- 3 stories of malls: 150x75m and 140x40m
- 8,13,14 store entrances as landmarks
- 150 photos for each landmark
- 182,184,151 CRC measurements
- 24 CWC measurements in story 3
  - Comprised of two parts
- 96,106,73 user traces along hallway
- ~7 traces inside each store



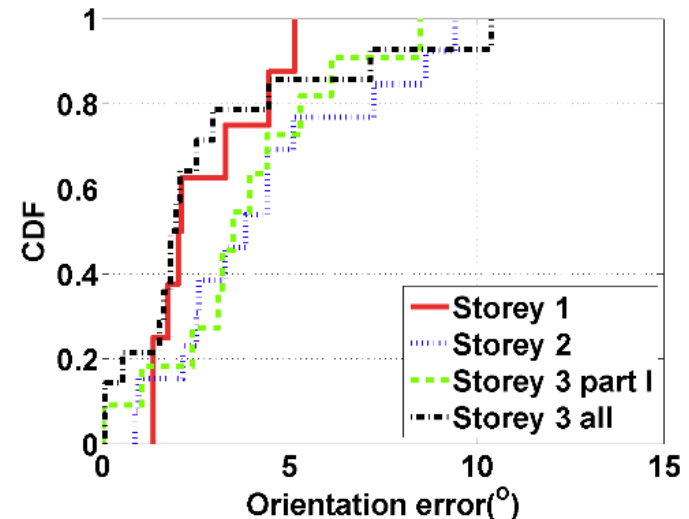
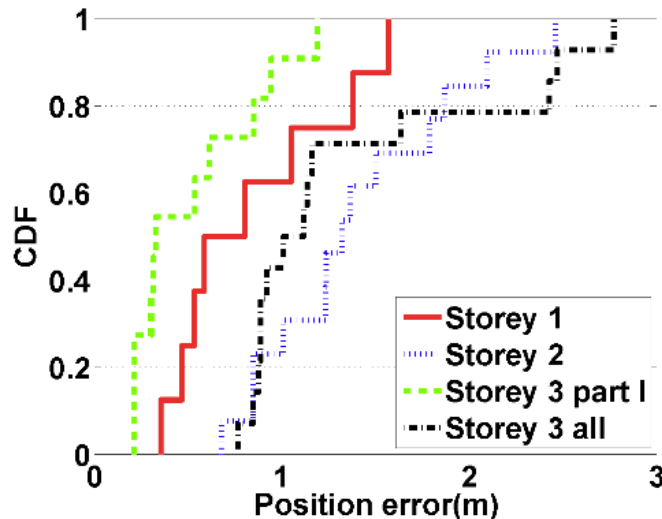
## ◆ Floor plans



# Reconstructed floor plans

## ◆ Landmark placement performance

- Store position error 1-2m
- Store orientation error 5-9 degrees

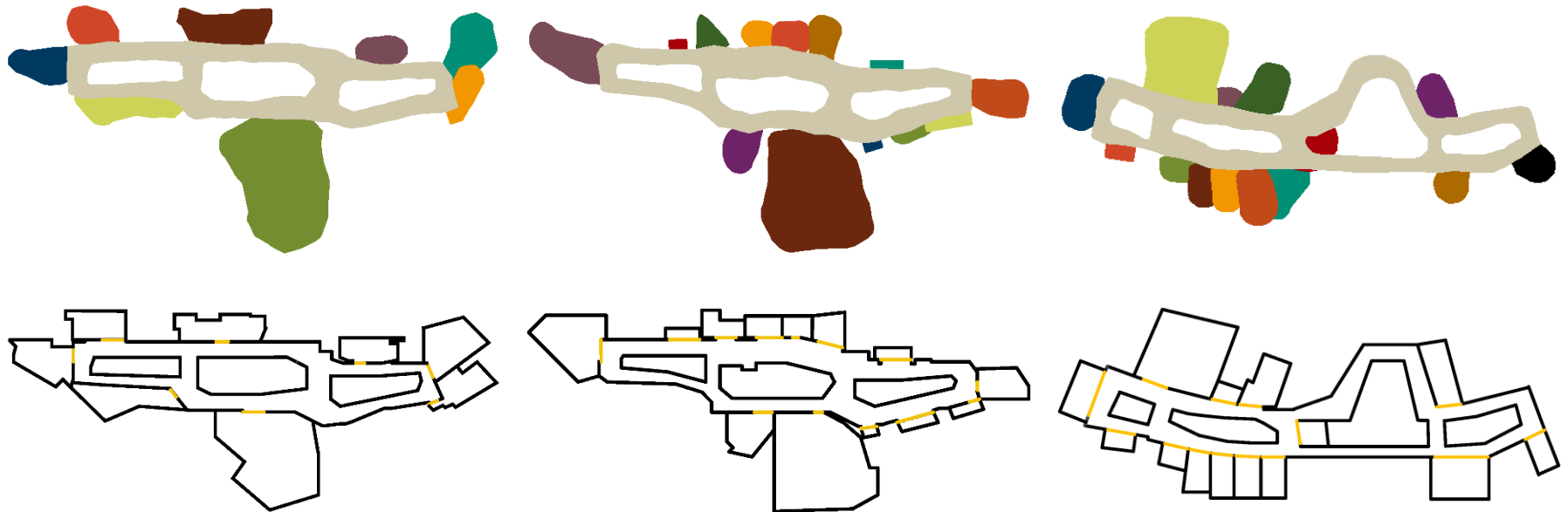


# *Reconstructed floor plans*

## ◆ Landmark placement performance

- Store position error 1-2m
- Store orientation error 5-9 degrees

## ◆ Constructed floor plans



# Detailed results

## ◆ Accuracy of floor plans

### ■ Root mean square error (RMSE)

- $X_i=(x_i,y_i)$ : 2D coordinates

### ■ Features

- Landmarks
- Hallway intersections

$$e_{RMS} = \sqrt{\frac{\sum_{i=1}^n (X_i^{map} - X_i^{test})^2}{n}}$$

RMSE of floor plan (m)



## ◆ Hallway shape

- Overlay the reconstructed hallway onto its groundtruth to achieve maximum overlap
- Hallway shape
  - Precision~80%, Recall~90%, F-score~84%

# Comparison with CrowdInside++

## ◆ Several assumptions of CrowdInside\*

- Sufficient numbers of anchor points (GPS, inertial, ..)
- Sufficient amount of traces passing through anchor points
- Distinctive WiFi signatures in different rooms

## ◆ Artificial improvements in CrowdInside++

- Double the number of anchor points; assume they are GPS-based
- All traces pass through adjacent anchor points
- Manually classify room traces

## ◆ Results of CrowdInside++

- Miss a few small-sized stores
- RMSE and maximum error: 4x of Jigsaw
- Hallway shape: ~30% less than Jigsaw



\* M. Alzantot and M. Youssef. Crowdinside: Automatic construction of indoor floorplans. In SIGSPATIAL, 2012.



# Comparison with CrowdInside++

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## ◆ Artificial improvements in CrowdInside++

- Double the number of anchor points; assume they are GPS-based
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## ◆ Results of CrowdInside++

## ◆ Causes

- Error accumulation of inertial-only approach
- Deterministic alpha-shape instead of probabilistic occupancy map



\* M. Alzantot and M. Youssef. Crowdinside: Automatic construction of indoor floorplans. In SIGSPATIAL, 2012.

# Related work

## ◆ Floor plan construction: relatively new problem

- CrowdInside, Jiang *et. al.*, Walkie-Markie, MapGenie
  - We combine vision and mobile techniques
  - We use optimization and probabilistic techniques

## ◆ SLAM

- Noisy and piece-wise crowdsensed data
  - No high precision special sensor: laser ranges, stereo/depth cameras
- Estimate landmark orientations

## ◆ 3D construction in vision

- Floor plans require only 2d

## ◆ Localization with vision techniques

- Sextant, OPS



# Summary

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- ◆ **Combine complementary strengths of vision and mobile techniques**
  - Vision: accurate geometric information, landmark only
  - Mobile: relative positions of landmarks, sketches of hallway/room shapes
  - Camera locations as anchor points
- ◆ **Optimization and probabilistic formulations for solid foundations and better robustness**
  - MLE: landmark placement
  - Minimum weight matching: hallway boundary construction
  - Occupancy grid map: hallway/room shapes



**Thank you!**

**Questions?**

